Temporary Workers Shares in Manufacturing Plants

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1. Introduction

The temporary help industry has grown rapidly over the last quarter century. Indeed. the industry's share of nonfarm employment has risen to nearly 2% from a base of less than 0.5% in the early 1980s. This growth has attracted much researcher on various topics surrounding temporary workers (Autor, 2003; Houseman, 2001; Sullivan and Segal, 1995, 1997; and etc.). However, there are few empirical studies examining firms' use of temporary workers as a way to accommodate fluctuations in production – one of the important roles that the temporary employment is believed to play.

Golden (1996) and Segal and Sullivan (1997) are two of the few papers examining such a topic based on macro economic data. Campbell and Fisher (2004) presents a theoretical model describing a firm's decision to adjust temporary and permanent workers and compare their calibration with aggregate level observations. There are only a few micro-data based empirical studies examining the relationship between the use of temporary workers and a firm's production volatility (Houseman, 2001).

One reason for the scarcity of empirical studies has been limited data. Even among confidential micro Census data sources such as the Annual Survey of

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Manufactures and the Census of Manufactures, it is rare that a survey collects data on the usage of temporary workers by business establishments. Such data limitations have prevented researchers from learning very much about the characteristics of firms that use temporary workers. As a result, most micro-level analyses of temporary workers have focused on demographic aspects of the topics (such as wage differentials between temporary and permanent workers, etc.) using data such as Current Population Survey. In such demographic data, information on firms where temps work is typically limited to only industrial category.

In this paper, we use plant-level data from the Plant Capacity Utilization (PCU) Survey ,which is conducted annually by the Census Bureau. These data are used by the Federal Reserve Board to produce estimates of capacity utilization rates for manufacturing and publishing industries. In 1998 the survey began collecting information of the number of temporary workers utilized by plants in the survey. However, thus far, only 1998 and 1999 micro-level data are available. Taking advantage of these newly available data, we examine how a plant's temporary worker share is associated with the plant's output fluctuations. In particular, we focus on the relationship between a plant's temporary worker share and the deviation of realized output from trend or expected output as well as the magnitude of plants' typical fluctuations. When a firm experiences an increase in demand, to the extent that it is expected to be temporary, the firm may be reluctant to hire additional permanent workers because of the costly process of firing such workers. In such situations, firms may rely on temporary workers to meet current employment needs. In addition, as we will see in Section 2, if firing costs are sufficiently high, greater dispersion in the distribution of output leads the firm to cap the number of perms at a lower level, and thus hire more temps. In our statistical analyses, we also control for plant characteristics such as plant size, age, industry.

Note that while micro-level studies examining firms' use of temporary workers are new, there are several micro-level studies on topics closely related to that of this paper. As an example, using plant-level data, Copeland and Hall (2005) examines how automakers accommodate shocks to demand by adjusting price, inventories, and labor inputs through temporary layoffs and overtime. Such factors are considered to be closely linked to a firm's decision to adjust temporary worker share. We intend to examine such interactions in future work.

In Section 2, we outline a model that motivates our empirical specification. In Section 3, we describe our data in more detail, and in Section 4, we discuss empirical implementation. In Section 5, we present our empirical results.

2. Model

In this section we discuss a stylized model of a plant's choice of temp worker share that is intended to help motivate and guide our empirical work. The model emphasizes the role of temporary services workers in accommodating fluctuations in output without increasing future costs associated with layoffs of regular employees.

Specifically, the model assumes that labor is the only factor of production and that in each period, the plant manager must hire an appropriate quantity of labor services, e_t, to meet an exogenously determined level of output, $y_t = f(e_t)$, where f is a standard, strictly-increasing production function. The required labor input can come from a combination of regular, or "perm," employees, p_t, and agency "temps," a_t, with the total quantity of labor services given by $e_t = p_t + \theta a_t$, where θ is a positive constant. The wage rates for perms and temps are w_p and w_a, respectively. In addition, the plant incurs firing costs of δ for each perm worker that is laid off. Thus, the plant's total costs in a period are $w_p p_t + w_a a_t + \delta \max(p_{t-1} - p_t, 0)$. We assume that future levels of output are uncertain and that the firm minimizes the expected present value of costs given a discount factor, $\beta = 1/(1+r)$.

Let the unit labor costs associated with hiring perms and temps be, respectively, $u_p = w_p$ and $u_a = w_a / \theta$. We assume that $\Delta u = u_a - u_p > 0$. That is, absent firing costs, temp workers would be more expensive to employ, either because their wage rate is higher ($w_a > w_p$), they are less productive ($\theta < 1$), or both. We further assume that the cost of firing a perm is greater than the (discounted) difference in unit labor costs, but less than a full period's wage, $\Delta u / \beta < \delta < w_p$. If $\Delta u > \beta\delta$, then the plant will never want to hire any temps; it will be cheaper to use perms even if it is certain that they will be laid off next period. The condition that $\delta < w_p$ is a convenient simplification that implies that the firm will not keep any idle workers on the payroll; keeping an idle worker on the payroll costs more than laying him off in the current period and may also increase layoff costs in the future. With this configuration of costs, the plant faces a tradeoff between using more perms, which lowers current wage costs versus using more temps, which may lower future firing costs.

Two Period Case

It is easiest to see logic of the model when there are only two periods. In this case, the plant is unconcerned about future firing costs in the last period. Thus it meets its entire labor need with permanent workers, $p_2 = f^{-1}(y_2)$, incurring costs $C_2 = w_p f^{-1}(y_2) + \delta \max(0, p_1 - f^{-1}(y_2))$.

The plant's choice is less trivial in the first period. Specifically, given y_1 and knowledge of the distribution of y_2, the firm chooses p_1 and a_1 to minimize total expected discounted costs taking into account how they will behave in the second period. Those total costs are $TC = w_p p_1 + w_a a_1 + \beta E[w_p f^{-1}(y_2) + \delta \max(0, p_1 - f^{-1}(y_2))]$. In order to meet the required level of production, $f^{-1}(y_1) = p_1 + \theta a_1$. Using the latter constraint, costs can be written as a function of p_1 alone,

$TC = u_p p_1 + u_a(f^{-1}(y_1) - p_1) + \beta E[w_p f^{-1}(y_2) + \delta \max(0, p_1 - f^{-1}(y_2))]$.

Thus, $\dfrac{dTC}{dp_1}(p_1) = -\Delta u + \beta\delta \dfrac{d}{dp_1} E[\max(0, p_1 - f^{-1}(y_2)]$.

Assume that the distribution of second period output is continuous with density $g(y_2)$ and distribution function $G(y_2)$. Then the expected number of layoffs in the second period given that p_1 perms were hired in the first period is

$L(p_1) = \int_0^{f(p_1)} (p_1 - f^{-1}(y_2)) g(y_2) dy_2$. Thus,

$L'(p_1) = (p_1 - f^{-1}(f(p_1)) g(f(p_1)) + \int_0^{f(p_1)} (1) g(y_2) dy_2 = G(f(p_1))$, which implies that

$\frac{dTC}{dp_1}(p_1) = -\Delta u + \beta\delta G(f(p_1))$. That is, increasing the number of perms by one (and thus lowering the number of temps by $1/\theta$) lowers costs in the current period by the difference between temp and perm unit costs (Δu), but raises expected firing costs in the second period by the product of the cost of firing a worker (δ) and the probability that the marginal worker will need to be fired ($G(f(p))$).

$G(y)$ and $f(p)$ are increasing functions. Thus, $\frac{dTC}{dp_1}(p_1)$ is also increasing. Moreover, $\frac{dTC}{dp_1}(0) = -\Delta u < 0$ and $\lim_{p_1 \to \infty} \frac{dTC}{dp_1}(p_1) = -\Delta u + \beta\delta > 0$. Thus there is a unique level of perms, $\overline{p}$, such that $\frac{dTC}{dp_1}(\overline{p}) = -\Delta u + \beta\delta G(f(\overline{p})) = 0$. See the top panel of Figure 1 for an illustration of the case in which the distribution of y_1 is uniformly distributed on the interval from y_{lo} to y_{hi} and $f(e)$ is linear.

On the one hand, if $f^{-1}(y_1) < \overline{p}$, then total expected discounted costs are decreasing in the number of perms all the way up to the value that completely satisfies the plant's employment need. Thus, in this case, the optimal number of perms is $f^{-1}(y_1)$ and the optimal number of temps is zero. On the other hand, if $f^{-1}(y_1) > \overline{p}$, then total expected discounted costs fall with p_1 until $p_1 = \overline{p}$, and then begin to rise. Thus the optimal number of perms is $\overline{p}$ and the optimal number of temps is $(f^{-1}(y_1) - \overline{p})/\theta$, the number necessary to meet the remaining necessary level of labor services. We can summarize the solution by writing the optimal numbers of first period perms and temps as $p_1^* = \min(f^{-1}(y_1), \overline{p})$ and $a_1^* = (f^{-1}(y_1) - p_1^*)/\theta$ where $\overline{p}$ satisfies $\beta\delta G(f(\overline{p})) = \Delta u$. In words, the plant hires perms up to a maximum value at which the expected discounted firing costs of hiring an additional perm are equal to the extra current wage costs of substituting an equivalent number of temps.

Lognormal Output Levels and Power Production Function

Suppose the distribution of y_2 is lognormal, $\log y_2 \sim N(\mu, \sigma^2)$ and the production function takes the power form, $f(e) = Ae^{\alpha}$. Then, the equation characterizing $\overline{p}$ is $\Delta u = \beta\delta G(f(\overline{p})) = \beta\delta\Phi(\frac{\log A + \alpha \log \overline{p} - \mu}{\sigma})$, where $\Phi(x)$ is the standard normal distribution function, and μ and σ^2 are the mean and variance of the log of the output distribution. Alternatively, $\log \overline{p} = \alpha^{-1}[\mu - \log A + \sigma\Phi^{-1}(\frac{\Delta u}{\beta\delta})]$. Because α and σ are positive constants and $\Phi^{-1}(p)$ is an increasing function, a higher value of the gap between temp and perm unit wage costs, Δu, increases the maximum perm employment level, leading to the use of fewer temps. On the other hand, a higher value of the firing cost, δ, lowers the cap on perm workers, leading to the employment of more temps. The impact of the dispersion parameter, σ, on the maximum number of perms depends on the ratio of the gap between unit wage costs and firing costs. If firing costs are sufficiently high that $\Delta u < \frac{1}{2}\beta\delta$, then $\Phi^{-1}(\frac{\Delta u}{\beta\delta}) < 0$ and greater dispersion in the distribution of $\log y_t$ will lead the plant to cap the number of perms at a lower level and, thus, hire more temps for a given level of output. The opposite is true if $\Delta u > \frac{1}{2}\beta\delta$.

That an increase in the uncertainty measure, σ, could lead to the use of fewer temps is, perhaps, somewhat counter intuitive. However, when firing costs are low, the plant will worry little about layoffs. As a result, it will hire so many perms that the probability of needing to lay off the last one will be greater than one half. Increasing the uncertainty in the number of workers needed in period 2 will move the probability closer to one half, which represents a decrease in the probability of needing to fire the marginal worker. This decline in marginal expected firing costs gives the plant the incentive to higher more perms. When firing costs are high, the effect of uncertainty works the other way. The fact that firing costs are high implies that the plant will keep the probability that the marginal worker needs to be laid off less than one half. Increasing uncertainty again leads to the probability moving closer to one half, but in this case, the probability increases. The increased probability that the marginal worker will need to be laid off in turn causes the plant to use fewer perms and more temps to produce the given output.

Note also that given the functional forms assumed in this section, the plant will hire a positive number of temps if $f^{-1}(y) = (y/A)^{1/\alpha} > \overline{p}$. This is equivalent to $\frac{\log y - \mu}{\sigma} > \frac{\log A - \mu + \sigma \overline{p}}{\sigma} = \Phi^{-1}(\frac{\Delta u}{\beta\delta})$, which happens with probability $1 - \frac{\Delta u}{\beta\delta}$.

IID Output Levels

If the plant's horizon is infinite, but the exogenous levels of required outputs over time are i.i.d. random variables, then we show in the appendix that the plant's optimal policy is essentially identical to that just derived for the first period of the two period model.[2] The intuition is that given future optimal behavior, the choice of p_t at time t will determine the number of perms laid off at time $t+1$. However, subsequent layoffs will depend on the independent choice of p_{t+1}, p_{t+2}, etc. and not p_t. Thus in considering the optimal choice of perms at time t, future firing cost considerations are identical to those in the first period of the two period model. That is, the marginal expected discounted firing cost associated with an increase in p_t is $\beta\delta G(f(p_t))$. Given that the plant is starting with a level of perms, $p_{t-1} < \overline{p}$, from the previous period, the marginal change in expected costs from employing an additional perm differs slightly from the two period case. This is because, if $p_t < p_{t-1}$, then increasing p_t saves on firing costs in the current period.[3] Thus, in the i.i.d. case, $\frac{dTC}{dp_t}(p_t) = -\Delta u - \delta I[p_t < p_{t-1}] + \beta\delta G(f(p_t))$, where $I[p_t < p_{t-1}]$ is an indicator function for $p_t < p_{t-1}$. This function has a discrete jump

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[2] The only qualification is that the plant must start with a level of perms that is less than or equal to $\overline{p}$, the cap derived in the last section. As long as this is the case, it will be optimal to follow the rule that $p_t^* = \min(f^{-1}(y_t), \overline{p})$. If this was not the case, that is, the plant started with $p_{t-1} > \overline{p}$, then it is possible for it to be optimal to choose $p_t > \overline{p}$. However, once a realization of the y_t comes in below $f(\overline{p})$, the rule $p_t^* = \min(f^{-1}(y_t), \overline{p})$ becomes optimal for the rest of time.

[3] In the two period case, we implicitly assumed that the plant started the first period with no perms. Thus it did not have to consider the effect of its decision on the number of perms laid off in the first period.

at $p_t = p_{t-1}$. However, it is still strictly increasing and given that $p_{t-1} < \overline{p}$, it still is equal to zero at $p_t = \overline{p}$. See the bottom panel of Figure 1.

Implications for Empirical Strategy

In the empirical section, we analyze the cross sectional determinants of the usage of temp workers. The simple model sketched here suggests that one important determinant will be the level of current output relative to the expectation of future output. When output levels are high relative to what is expected in the future, the model suggests that firms will tend to use more temps in order to avoid firing costs. We also look at the effects of cross-plant variation in the uncertainty of future output. The model says that, in principle, higher uncertainty could either increase or decrease the usage of temp workers. In the empirical work we control for industry as well as characteristics such as plant size and age that may proxy for variation in the level of firing costs and temp wage differentials that the model says should also influence the usage of temps.

3. Data

The main data set for this study is the survey of Plant Capacity Utilization (PCU), which is used by the Federal Reserve Board to estimate capacity utilization rates of manufacturing and publishing plants.[4] In addition to variables related to plants' operation status and capacity utilization, the survey collects data on work patterns by shift, including production worker numbers and hours worked as well as overtime hours. Such information is provided for each of the shifts that a plant operates during the fourth quarter of each year. Since 1998, the survey has collected temporary production worker number and hours worked, key variables in our study. Currently the 1998 and 1999 PCUs are available for this study.

While approximately 17,000 plants are surveyed each year, many plants are out of our focus or do not respond to the key items for our study. In particular, in our empirical work, we include only manufacturing plants that are in operation and that provide valid answers for key employment variables including the number of temporary production workers. We also exclude plants that reported inconsistent responses for key variables.

Among them, we further select plants, for which we can calculate measures of the level and volatility of production. As we describe below, we calculate such measures using annual output data from Annual Survey of Manufactures (ASM) and Census of Manufactures (CM). Thus, our sample is limited to the plants which previously appeared in the ASM-CM panel for at least a certain number of years. Combining both years of available PCUs leaves us with about 5,500 plants. Appendix A.1 provides more details about which plants are included in our sample. Compared to the full 1997 CM, plants in our PCU sample are much older and larger in terms of both output and employment.

While the PCU provides employment and hour data for each shift, examining the allocation of perm and temp workers between different shifts is beyond the scope of this paper. In what follows, we focus on a plant's overall use of temporary workers for all shifts in total. In our sample, the fraction of plants employing a positive number of temporary production workers in a particular year is about 40%. The remaining 60% of plants operate without using any temporary workers. This is consistent with our stylized model, which predicted that when output is below a certain threshold, a plant uses only permanent workers.

4. Empirical Implementation

In the model, we outline how a plant's usage of temporary workers is associated with the difference between its current and expected future production levels, which we denote by d, as well as the average uncertainty associated with its production level, which we denote by σ. To test the relationship between these variables, we first estimate probit models that relate a plant's likelihood of using temporary workers in a given period to its characteristics. More specifically, let us denote the net benefit for a plant of hiring temps by Z_{it}^*.

$Z_{it}^* = (d_{it}, \sigma_i, X_{it})\boldsymbol{\lambda} + u_{it}$, (1)

where d_{it} is the deviation of a plant's actual output from the future output, and σ_i is the average level of uncertainty of the plant, X_{it} is a vector of other control variables,

[4] http://www.census.gov/econ/overview/ma0500.html (August, 2006)

including plant age and age squared,[5] 2-digit SIC industry dummies, and a survey year dummy. Assuming that a plant hires temporary workers when $Z_{it}^{*} > 0$, we estimate (1) by maximum likelihood.

We also estimated tobit models that utilize information on the share of temporary workers. In our sample, among plants with some temps, the distribution of temporary worker shares has a mean of about 10%, but is heavily skewed toward to the left. In order to avoid such skewness, we calculate $S \equiv \log(\frac{TempShare}{1-TempShare})$. This transformed variable has a much more symmetric distribution, making it more appropriate for use as a dependent variable in the tobit analyses. Analogously to the probit models, we estimate;

$S_{it} = (d_{it}, \sigma_i, X_{it})\tilde{\lambda} + \tilde{u}_{it}$, (2)

where S_{it} is censored at the value with the smallest positive temp share for those plants without any temp.

Measure for d and σ

Data

To measure d, the deviation from the future output level and σ, the uncertainty for each plant, we use the time series data of plant total value of sales (TVS) from Annual Survey of Manufactures (ASM) and Census of Manufactures (CM). The CM is a population survey and is conducted every five years. In contrast, the ASM is a sample survey and is conducted annually.[6] We observe the TVS of all manufacturing plants in a Census year as long as they exist, but in off-Census years, we only observe the TVS of plants sampled for the ASM. Using a plant identification number, which is given based on a physical location of the plant, we create ASM-CM plant-level unbalanced panel data. Note that, to use a consistent plant identifier, we limit ourselves to the ASM and CM observations

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[5] Plant age is calculated based on the variable "firstyear" in the LBD, which is essentially the first year that a plant is found in linking the plant time series data for the LBD. While LBD starts from 1976, "firstyear in the LBD distinguish plants that appear in 1976 and those appeared before 1976; the earliest year we can track a plant back from the LBD is 1975.

[6] The ASM is performed as a part of CM in the Census year. Plants in ASM samples are asked to fill a longer questionnaire.

from 1976 and after.[7] We focus on real TVS values by employing the TVS deflator for each of 4-digit SIC calculated by Bartelsman, Becker, and Gray.[8]

Unfortunately, monthly and quarterly series on plant level TVS are not available in the ASM or CM. Thus we analyze output fluctuations at the annual frequency. This makes it impossible to analyze the need for seasonal temporary workers.

Note also that for establishments with employees, we can observe their annual employment in the LBD. However, the LBD does not provide TVS. In addition, like many other surveys, the employment in the LBD data is employment on payroll (i.e. permanent employment) and does not include workers employed by temporary service firms. To the extent that a plant uses temporary workers to accommodate output fluctuations, variation in permanent employment would under represent output fluctuation. Any unobserved or uncontrolled factors that increase a plant's use of temporary workers may be translated into the lower level of the plant's permanent employment fluctuation. Thus, in this paper, we use TVS data to capture output fluctuation.

Measure

To capture d and σ, we estimate three models for expected output using the ASM-CM panel. As a measure of the degree of uncertainty, we use the standard deviation of the residual from the model, assuming that the average uncertainty level that a plant has experienced remains in future. As we discuss in more detail below, we also decompose d into two components. One is the deviation of the realized output from its expected level of the year, which we denote by $\tilde{d}$; this can also be considered as shock or surprise in output relative to expectations. The other is a factor summarizing the expected/trend growth rate. It may be instructive to see how these components are separately related to a plant's temp share.

[7] As a plant identifier, we use LBD number, which is a revised version of Permanent Plant Number (PPN) used in much research on manufacturing data base such as Longitudinal Research Data (LRD). Like PPN, the LBD number does not change at the event of merger and acquisition and is specific to a plant physical location. LBD number is created as a part of the effort for a Census to create the LBD, which review and update the longitudinal linkage as well as the operation status of the establishments/plants in the SSEL. While the Census of Manufacturing goes back to 1963, the LBD starts from 1976.

[8] The data sets for the deflators through 1991 are posted at http://www.nber.org/nberces/nbprod96.htm. We thank Randy Becker for letting us use the preliminary version of the TVS deflators for the later period.

First (Model 1), we use a simple mean of the log TVS in the ASM-CM data as the expected output. In this case, d is simply the deviation of value for the year from its average and can also be considered as shock; $d_{it} = \tilde{d}_{it}$. σ_i is just the standard deviation of log TVS. If plant's production levels are i.i.d. random variables, these measures adequately reflect the long-run level and volatility of the plant's output.

However, there are some obvious reasons to question the adequacy of such measures. First, the data are unbalanced, with plants being observed in different sets of years. Because years differ in their volatility, we also estimated models including a measure of the state of the macroeconomy in the particular periods that a plant is included in the sample. The resulting measure of σ_i should be purged of these sample year effects. In addition, it is possible that plant output may not be i.i.d., and there might be factors, such as age, which is systematically associated with a plant's output level. Since we do not observe TVS for all the years that a plant exists, the simple mean of TVS observed in our sample would depend on where in a life cycle the plant is when it is included to the sample. Considering these issues, we estimate the following specification (Model 2);

$$ltvs_{it} = \alpha_i + \beta_i T + \gamma n_t + \varepsilon_{it}, \quad (3)$$

where $ltvs_{it}$ is log TVS of plant *i* in year *t*. T captures a plant specific time trend that absorbs any linear effect of plant age, and n_t is a macroeconomic variable that captures business cycle. As n_t, we use the deviation of log real GDP from log potential GDP provided by the CBO. Note that in this model, expected future output depends on expectations of n_t. However, γn_t is common across plants and thus does not affect relative expectations across plants. Thus we simply use the realized value for n_t in calculating the expected outputs. σ_i is the standard deviation of the error terms and does not reflect a particular period or a particular part of a plant's life cycle that the plant appears in the ASM-CM sample.

Note that in this specification, unlike Model 1, the expected output changes over time, and the deviation of output from the expected future level is no longer the same as the deviation of the current level from previous expectations. More specifically, we can write

$$
\begin{aligned}
d_{it} &\equiv ltvs_{it} - E[ltvs_{it'}] \\
&= \{ltvs_{it} - E[ltvs_{it}]\} - \{E[ltvs_{it'}] - E[ltvs_{it}]\}
\end{aligned}
$$

where $ltvs_{it'}$ is log TVS in future period t'. The term in the first bracket is the deviation from the output level expected for the current period, $\tilde{d}$. To the extent that a plant's current output level exceeds from the trend or what is expected, we expect the plant to be more likely to hire temporary workers and have greater temporary worker share. If a plant finds the current output level below trend or expected levels and decides to lower the level of labor, it would layoff temps before it dismisses permanent workers. The term in the second bracket represents the expected growth rate, and under the specification in (3), it is equal to β_i. If firing costs are an important consideration and fast growing plants are less likely to need to layoff workers in the future, one might expect faster growing plants to hire a lower share of temp workers. In our empirical examination, we include shock ($\tilde{d}$) and trend growth (β_i) separately.[9]

Next, we estimate a more elaborate model (Model 3) in which a plant forms its expectation of its future growth rate based on the current realized growth rate. We also control for age effects in a quadratic form. We again control for the change in macroeconomic conditions. Denoting the growth rate of TVS (the change in the log of TVS) by $gtvs$, we estimate;

$$gtvs_{it} = \tilde{\beta}_i + \rho_i gtvs_{it-1} + (age_{it}, age_{it}^2, dn_t)\tilde{\boldsymbol{\gamma}} + \upsilon_{it}\,, \quad (4)$$

where $dn_t \equiv n_t - n_{t-1}$. Unlike Model 2, here, a plant uses the past realized output level to form its expectation for the future output level. Moreover, any uncertainty is what a plant could not foresee based on the previous year's information. In a sense, here, we implicitly assume that a plant sets the permanent employment level based on its expectation on the next year output that is based on the current realized output level. Thus, we write;

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[9] More specifically, we can write $E[ltvs_{it'}] - E[ltvs_{it}] = \beta_i(t'-t) + \gamma(n_{t'} - n_t)$. However, only β_i varies across plants. Thus, relative differences in average growth rates are essentially summarized by β_i.

$$
\begin{aligned}
d_{it} &\equiv ltvs_{it} - E_t[ltvs_{i,t+1}] \\
&= \{ltvs_{it} - E_{t-1}[ltvs_{it}]\} - \{E_t[ltvs_{i,t+1}] - E_{t-1}[ltvs_{it}]\}
\end{aligned}
$$

where $E_{t-1}[ltvs_{it}] = ltvs_{it-1} + E_{t-1}[gtvs_{it}]$.

The term in the first bracket is the shock, $\tilde{d}$, due to unforeseeable events after a plant observes the output/growth rate in the previous year, which we capture by the residual term from (4); $ltvs_{it} - E_{t-1}[ltvs_{it}] = gtvs_{it} - E_{t-1}[gtvs_{it}] = \upsilon_{it}$. We can rewrite the term in the second bracket as;

$$
\begin{aligned}
&E_t[ltvs_{i,t+1}] - E_{t-1}[ltvs_{it}] \\
&= ltvs_{it} + E_t[gtvs_{it+1}] - (ltvs_{it-1} + E_{t-1}[gtvs_t]) \\
&= gtvs_{it} + E_t[gtvs_{it+1}] - E_{t-1}[gtvs_t] \\
&= v_{it} + E_t[gtvs_{it+1}].
\end{aligned}
$$

In the steady state, the growth rate is increasing in β_i and ρ_i.[10] We include both measures separately when we estimate (1) and (2).[11]

Using the measures we described above, we estimate probit (1) and tobit (2) models for temp share based on each of the above specification for output levels. Note that while we have only annual series of the TVS to estimate these above models, the PCU provides a plant's information of 4th quarter including the 4th quarter TVS. Using such information, we capture shock to the 4th quarter output as a deviation of the annualized 4th quarter output from the expected annual output from the ASM-CM panel; $\tilde{d}_{it} \equiv \ln(4 \bullet tvs_{it4Q}) - E[ltvs_{it}]$. This may be more closely related to the temporary employment share reported for the 4th quarter of a given year.

[10] In this specification, $\tilde{\beta}_i$ is time invariant component of growth rate specific to a plant and ρ_i reflect the correlation among growth rates across time. Given ρ_i, $\tilde{\beta}_i$ corresponds to β_i in (3) in the sense that both summarize the time invariant relative difference in average growth across plants. If we ignore the random component in (4), the steady state growth rate is $\frac{\tilde{\beta}_i + \mathbf{A_t\gamma}}{1-\rho_i}$, where $\mathbf{A_t}$ is the vector of age and macro economic variables. A greater ρ_i is associated with a greater steady state growth rate.

[11] Age and macro economic variables also influence the growth rate. Age variables are controlled for in (1) and (2), and the macro economic variable is the same across plant for a given year. A dummy variable for a survey year is included.

Applying each model to our ASM-CM panel, $\tilde{d}$ is almost symmetrically distributed between -1 to 1 for most plants. We exclude plants for which $\tilde{d}$ is below -1 or above 1, considering them as outliers. Our measure of uncertainty, σ, is distributed between 0 to 1 except for some outliers, which are again excluded.

5. Results

Table 1 shows the results. Note that while our simple model does not provide any implication on the relationship between a plant's temporary worker share and its size, other considerations suggest that the scale of plant's operation may influence its tendency to employ temps. Thus, we perform probit and tobit analyses with and without controlling for plant size (log. annualized 4th quarter output). The qualitative results for our key variables are the same in either case. Table 1 shows the results where we control for plant size.

In both the probit and tobit analyses, $\tilde{d}$ and σ are estimated to have positive coefficients, and the coefficients are statistically significant in most specifications. To help interpret the results, note that based on Columns 1 to 3 of the Table 1a for plants with average characteristics, a positive 50% deviation of realized output from expected levels implies a 4 to 8 percentage point increase in a plant's probability of employing temporary workers. In the tobit results, a plant with an initial temp share of 10% that has a positive 50% deviation of realized output from expected output can be expected to experience an increase in temp share to between 15% to 20%. Apart from the effect of d, a greater average magnitude of uncertainty further increases the likelihood for a plant to employ temporary workers. A plant that has 50% higher uncertainty than the average plant is predicted to have a probability of using temps that is .035 to .086 greater than the average plant. For a plant with an initial temp share of 10%, the share increases to 17% to 23%.

Next we add the interaction term between $\tilde{d}$ and σ (see Column 4 to 6). The coefficients are not significant except for the Model 2 in the probit analysis (Colum 5 in Table 1a). For a given $\tilde{d}$ in a particular year, plants with higher average uncertainty are much more likely to use temporary workers than plants with lower average uncertainty.

Here we provide an explanation. As compared to plants with low average uncertainty, plants with high average uncertainty may be more likely to consider a given shock as temporary and not persistent. Thus, they may tend to adjust labor by the number of temporary workers rather than permanent workers in response to the shock.

In Columns 7 and 8, we explore how expected output growth is associated with a plant's use of temporary workers. In both Models 2 and 3, the results indicate that greater expected output growth is associated with greater use of temporary workers. This may be counter intuitive. One may consider that the greater expected growth reduces the probability of firing permanent workers in future, which in turn decreases a plant's use of temporary workers. However, the results from both probit and tobit analyses do not seem to be consistent with this view. Note, however, that our finding may be consistent with the idea that when the economy starts to recover, we tend to observe the increase in temporary workers prior to that of permanent workers. A common explanation for this is that plants wait till they are certain about the recovery for hiring permanent workers. While we include a measure of average uncertainty in our models, a more elaborate measure of uncertainty that changes over time may be necessary to capture the possibility that uncertainty is particularly high when expected output growth is high. It is also possible that our measure of average growth may be capturing growth at too short-run of a horizon.

Finally, we would like to note that some industry dummies obtain significant coefficients. In addition to the effect of output fluctuations, there are various factors such as unionization rate, seasonality, etc that would influence a plant's temporary worker share. The industry dummies might be reflecting such factors.

Table 1

a. Probit Analyses: dF/dX

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Model1	Model 2	Model 3	Model1	Model 2	Model 3	Model 2	Model 3
$\tilde{d}$	0.158***	0.083***	0.100***	0.141***	0.015	0.087**	0.057	0.097**
	[8.70]	[4.27]	[4.82]	[3.64]	[0.34]	[2.06]	[1.29]	[2.28]
σ	0.070*	0.172***	0.097*	0.059	0.191***	0.099*	0.121**	0.114*
	[1.81]	[3.29]	[1.66]	[1.33]	[3.53]	[1.68]	[2.20]	[1.89]
$\sigma \times \tilde{d}$				0.035	0.193*	0.042	0.239**	0.076
				[0.50]	[1.70]	[0.34]	[2.09]	[0.61]
β							1.044***	0.916***
							[7.33]	[7.78]
ρ								0.066***
								[2.68]
Log. Annualized 4^{th} Q. TVS	0.014**	0.038***	0.037***	0.014**	0.038***	0.037***	0.020***	0.023***
	[1.97]	[5.89]	[5.67]	[1.96]	[5.96]	[5.68]	[2.90]	[3.45]
Age variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of obs in ASM-CM panel	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5431	5431	5431	5431	5431	5431	5431	5431

Robust z statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

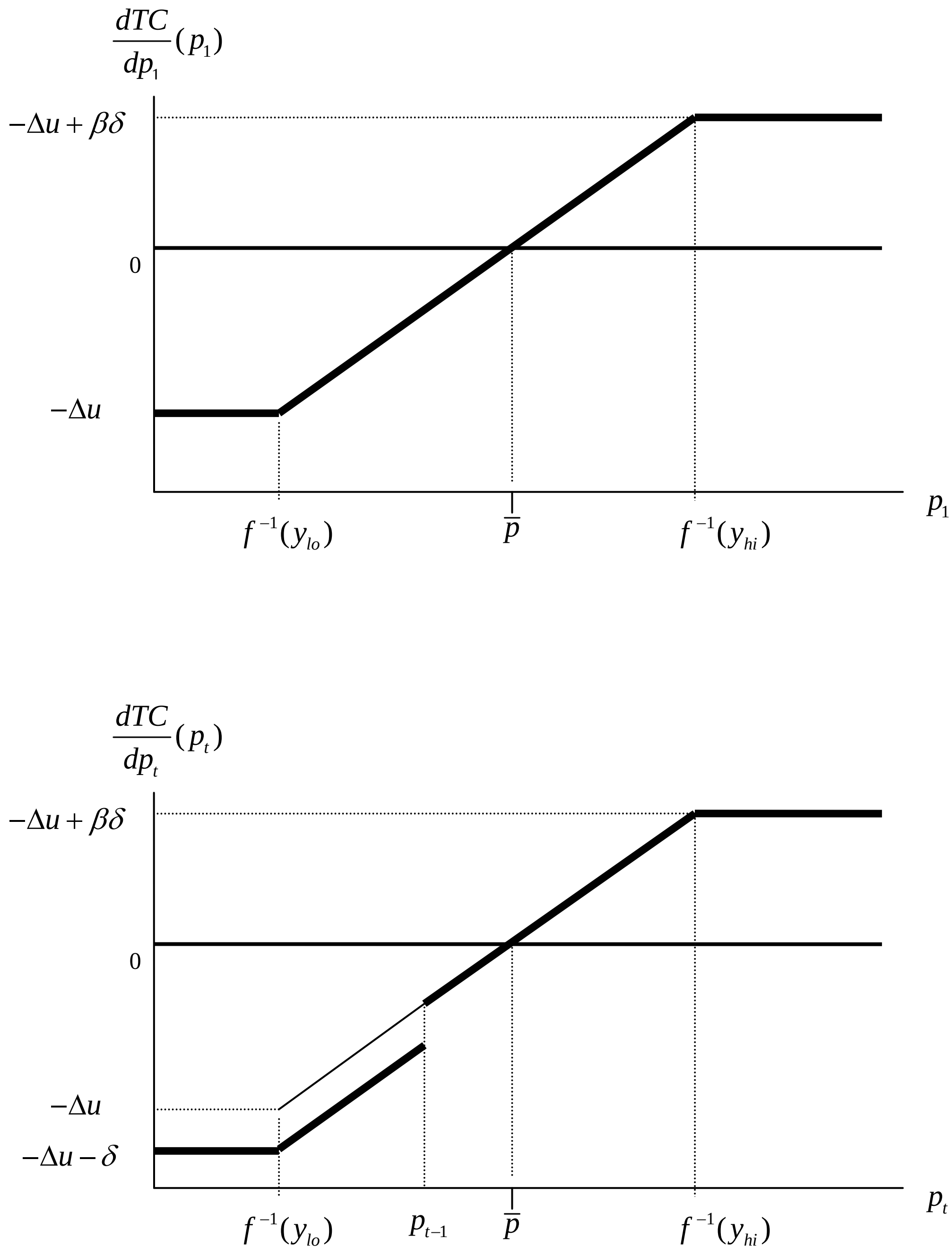
b. Tobit Analyses:

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Model1	Model 2	Model 3	Model1	Model 2	Model 3	Model 2	Model 3
$\tilde{d}$	1.683***	0.912***	1.079***	1.651***	0.316	1.087**	0.765*	1.194***
	[9.01]	[4.63]	[5.11]	[4.19]	[0.72]	[2.57]	[1.74]	[2.85]
σ	0.800**	1.998***	1.385**	0.778*	2.125***	1.384**	1.362**	1.494**
	[2.05]	[3.76]	[2.33]	[1.70]	[3.95]	[2.33]	[2.50]	[2.51]
$\sigma \times \tilde{d}$				0.065	1.668	-0.026	2.116*	0.348
				[0.09]	[1.52]	[0.02]	[1.93]	[0.30]
β							10.809***	9.709***
							[7.73]	[8.42]
ρ								0.665***
								[2.62]
Log. Annualized 4^{th} Q. TVS	0.098	0.366***	0.358***	0.098	0.371***	0.358***	0.171**	0.202***
	[1.37]	[5.46]	[5.30]	[1.37]	[5.52]	[5.30]	[2.39]	[2.91]
Age variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of obs in ASM-CM panel	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5431	5431	5431	5431	5431	5431	5431	5431

Robust z statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1: Determination of the cap on perm workers: Two period and infinite horizon i.i.d. models



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Appendix

A.1 Our sample based on the PCU data

In the questionnaire, for each shift, plants are asked to report the total number of production workers, temporary production workers, total hours worked by production workers, hours worked by temporary workers, and over time hours (See Item 3 in the questionnaire). We consider that a plant operates a given shift if it reports positive total production workers for the shift, which are defined to include temporary workers in the instruction of the questionnaire given to the plant. Among plants operating a particular shift, however, many left the information on temporary production workers unfilled, and often, such plants do not provide the temporary worker number for any shifts. In such a case, it is not clear whether the plant did not use temporary workers or did not fill out the item. Since the instruction for the PCU survey explicitly tells them (with several examples) to write zero when the plants operate a given shift but do not use temporary workers, we consider that they did not fill out the item. We exclude plants with missing temporary employment for any of their active shifts (i.e. shifts for which the plant reports positive total number of production workers).

In addition, by definition given in the instruction, when a given shift exists, the total number of production workers should be greater or equal to the number of temporary workers. We exclude plants with any inconsistency regarding these figures. We also exclude a few plants reporting the same number for both total and temporary workers for some shifts. It is possible that these shifts are actually supported by only temporary workers. However, such incidents are rare and we cannot tell whether these are miss data entry.

Once we clean the PCU data, we limit the sample to those for which we can estimate $\tilde{d}$ and σ based on ASM-CM sample as discussed above. Among models we discussed in Section 3, Model 3 put more restriction to our sample. In Model 3, for a plant to be included in estimation, the plant has to appear in consecutive 3-years at least once in ASM-CM panel. However, plants with only one or two consecutive 3-year observations typically become outliers in terms of the estimated values for $\tilde{d}$ and σ. Thus we limit our sample to plants that appear 3 year consecutively at least three times. We then match these plants with the cleaned PCU sample and use the observations of the plants for which we have the estimates our key variables. Some further outliers are excluded.